SCUOLA DI INGEGNERIA INDUSTRIALE
E DELL'INFORMAZIONE

Executive Summary of the Thesis

Co-simulation environment to assess human perception of Cooperative Connected and Automated Vehicles: calibration of the microscopic traffic simulation

Laurea Magistrale in Mechanical Engineering - Ingegneria Meccanica

Author: Álvaro Varela Daniel

Advisor: Prof. Gianpiero Mastinu

Academic year: 2022-2023

1. Introduction

During the last decades, to address safety and fluency problems related to the increasing number of vehicles on the road, different solutions have been implemented. Among these solutions, we can find the introduction of dedicated infrastructure to address conflicts in intersections, such as roundabouts; and, more recently, the introduction of Cooperative Connected and Automated Vehicles (CCAV) which offer promising results [2]. However, the introduction of this new technology faces challenges such as safety in complex urban environments, like roundabouts, and lack of acceptance by other road users. To address this, it is important to test the solutions prior to introducing them into the market. However, testing of innovative technologies is expensive and potentially dangerous. To overcome these issues, simulation is a good alternative, specially at early stages of development. However, testing CCAV related technologies includes different challenges, among which the communication between all the required components is key. To overcome this difficulty, the AI@EDGE architecture is used.

The European project AI@EDGE proposes a system architecture that combines 5G, Artificial Intelligence (AI) and edge computing which is validated through 4 different industry relevant use cases [1] ((1) Cooperative Connected Automated Vehicles (2) Secure and resilient large IoT networks (3) Drone supervision of linear infrastructures (4) In-flight entertainment systems). The use case in which the thesis is framed is UC1: Virtual validation of vehicle cooperative perception. The specific implementation of the architecture is shown in figure 1

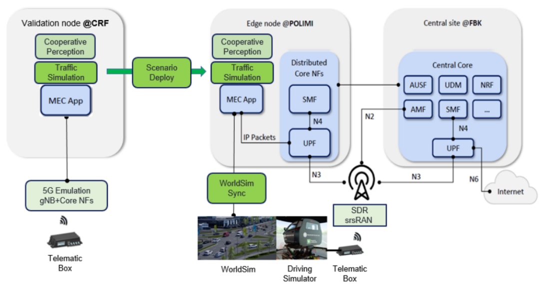

Figure 1: Architecture of the UC1 [1]

In the shown scheme, we can see the different components that are needed for the proposed tests. The first component is the telematic box that allows to communicate the position of the vehicles to the network. The second component is the driving simulator, that involves introduc-

ing the human in the loop using the driving simulator at the DriSMi facilities. The third component is the traffic simulator, that provides the information of the simulated traffic that interacts with the driver in the driving simulator. This traffic is composed by a mix of automated vehicles, controlled with a pre-trained AI policy and cars that represent human-driven vehicles using a calibrated Car Following Model. In the scope of this thesis the used traffic simulator is Simulation of Urban MObility (SUMO) [3].
The main objectives of this thesis include designing and calibrating the traffic simulation based on real traffic conditions, that is then used to train the AI-policy; aligning the scenario of the traffic simulation with that of the driving simulator; and assessing how drivers perceive the safety and fluency of the traffic with varying levels of automated vehicles in the simulation.

2. Traffic simulation calibration

On previous steps of the project, a theoretical traffic scenario had been designed to perform preliminary tests and gain understanding of possible difficulties. This scenario included a three-legged roundabout based on which an AI-policy was trained and tested using the driving simulator. However, the project requires to use a real traffic scenario to improve the validity of the obtained conclusions. This scenario is a four-legged roundabout located in Milan with sufficient levels of flow as to observe congestion and queue formation at the entries.

2.1. Data acquisition

The data acquisition was performed on 14th December, 2022. To do it the license plates of entering and exiting vehicles were collected, as well as the maximum and average number of vehicles in queue and the number of pedestrians crossing the legs of the roundabout. This process was done for 1 hour divided in 6 10-minutes periods. As a result, for each period an Origin-Destination (OD) matrix for each vehicle type, maximum and average queue lengths were obtained. The OD matrices are the input for the simulation process and the maximum queues are the output and the difference between the simulated queues and the real queues constitutes our Measure of Performance (MoE).

2.2. Network and demand creation

To perform a simulation using SUMO, two main components are required: network and demand. One of the available options to create a network allows the user to import a scenario from available OpenStreetMaps (OSM) information. This simplifies the process and helps to have a realistic network, although some modifications are needed to obtain a satisfying result. These modifications include adding pedestrian crossings, bus stops, missing lanes and adjusting the width of different roads, as well as deleting not relevant parts of the infrastructure. We introduced the demand using a Poisson distribution for each of the elements of the different OD matrices, where bicycles and motorcycles were transformed into cars using a conversion factor, while maintaining heavy vehicles and buses. Using a Poisson distribution introduces variability into the simulation, but we did not have enough information about entering times of the vehicles to use a different approach and uniform distributions are not realistic in traffic simulation. The other source of stochasticity in the simulation is the individual desired maximum speed which follows a normal distribution.

2.3. Convergence and sensitivity analysis

To account for stochasticity, it is necessary to repeat the simulation over different seeds that command the initialization of the random processes. To assess the minimum repetitions needed, we performed a convergence analysis. To reduce the computational burden of this process, we used a reduced simulation, looking at the first 10 minutes, using the real data available. We repeated the simulation for 50 different seeds and looked at the variability between outputs, and decided that it was sufficiently diminished with 5 simulations, although ideally we would have done 15. The computational cost was the main reason to keep a low number of repetitions, since the time step of the simulation needs to be 0.005 seconds to be able to work in the cosimulation scheme with the driving simulator. To decide which parameters are more influential we changed parameters individually and looked at the impact on the queue length, after this, we selected the parameters that according to the ANOVA test led to significant differences for at least one of the outputs.

2.4. Calibration results and discussion

The selected parameters refer to the parameters controlling the Intelligent Driver Model (IDM) and the Junction Model implemented in SUMO. The IDM is selected among the available CFMs in SUMO because of its reduced number of parameters, its easy interpretability and because it tends to outperform other CFM according to the literature. The 8 modified parameters are the ones coming from the ANOVA analysis, and the ranges in which they vary are set looking at the physical meaning of each of the parameters. To select the best parameters multiple sets of parameters are generated using the quasi-random Sobol sequence. We performed the simulation for 1000 sets of parameters and selected the set of parameters that reduced the Mean Square Error (MSE) looking at 20 outputs of the simulation, 1 queue for each of the 4 legs during the last 5 periods (the first one was excluded due to the presence of clear outliers). We divided the time periods in two groups, one including periods 2,3 and 4 and the other periods 5 and 6, and selected the set of parameters that provided the best compromise of minimum Mean Square Error for both groups. The parameters of the best set are shown in table 1

Best parameter set

Parameter	Default	Best set
jmTimegapMinor	1 s	1.7792 s
jmCrossingGap	10 m	1.3545 m
Impatience	0	0.1282
accel	2.6 m/s2	1.76 m/s2
decel	4.5 m/s2	4.29 m/s2
tau	1 s	1.3472 s
minGap	2.5 m	1 m
actionStepLength	0.005 s	0.505 s

Table 1: Parameter set with minimum MSE

The first three parameters refer to the Junction Model implemented in SUMO, and represent in order: the time gap required to pass in front of a car, the distance to a pedestrian before stopping, and the willingness to enter the intersection and make vehicles inside brake. The last 5 parameters are related to the IDM: *accel* and *decel* represent the maximum desired acceleration of the driver, *tau* is the time headway to a leading vehicle, *minGap* represents the minimum distance when standing and *actionStepLength* acts as a pseudo reaction time, representing the time step between decisions of the driver. In figure 2 we present the results looking at the total queue for each of the analysed periods considering all the entries together.

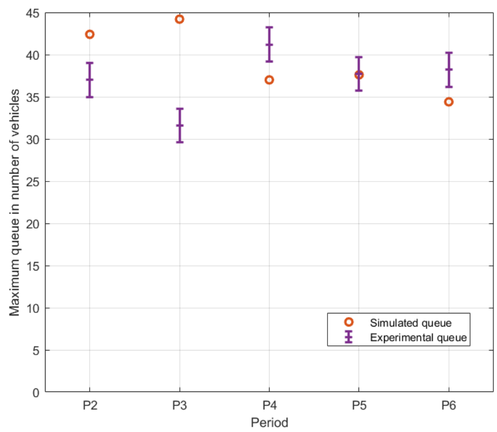

Figure 2: Real and simulated queues comparison

When looking at the different entries individually, we confirmed the overall good performance of the selected parameters, although the model captures some entry queues better than others. This could be linked to errors when recording the data or specific traffic situations that our simulation is not able to capture. To enhance the validity of the model it could be possible to repeat the data acquisition and check how the model performs.

3. Co-simulation

The co-simulation scheme involves being able to display the vehicles of the traffic simulation in the driving simulator and to introduce the vehicle driven by a human in the driver simulator into the traffic simulation, in a way that the simulated vehicles are able to interact with it. SUMO with the Traffic Control Interface (TraCI) allows to retrieve information from all the vehicles of the simulation as well as to change the state of the vehicle. To do this, it is fundamental that both scenarios, the traffic simulation and the driver simulator, are completely aligned.

Prior to aligning the scenarios, we modified the

SUMO network, merging one of the lanes that were previously separated to simplify the scenario for drivers that are not previously familiar with it, deleting a possible source of driver errors; and reducing the length of the legs to reduce the number of vehicles present in the simulation simultaneously, reducing the computational burden so that the system is able to perform the simulation in real time.
After modifying the SUMO network it is possible to, through an intermediate format, open the scenario in the software required to create the scenario for the driving simulator. Then, the scenario is modified adjusting the width of the roadway of the roundabout, so the driver cannot be outside of the traffic simulation domain, while maintaining a sufficiently realistic scenario and adding elements such as buildings and trees that improve the realism of the scenario and help the driver perceive the speed. This final scenario can be seen in figure 3.

Figure 3: Driving simulator scenario

3.1. Tests and results

Once the scenarios are aligned, we performed some tests with non-professional drivers. The drivers were asked to enter the roundabout from the four different legs and leave the roundabout taking the third exit. They were exposed to two different traffic situations regarding the mix of automated and non-automated vehicles, CCAV penetration of 20% and 80%. They were asked to assess the fluency and safety of the different situations using a questionnaire. The number of participant was 10 and the results in terms of preferences are shown in table 2.
According to this results, we can see that the policy performs well not only according to the predefined KPIs but that it is also accepted and

Scenario preferences

Answer	Safety	Smoothness	Overall
Definitely 20%	0	1	0
Partially 20%	2	3	3
Partially 80%	2	4	3
Definitely 80%	6	1	4
No difference	0	1	0

Table 2: Preference questionnaire results

perceived as an improving the traffic conditions.

4. Conclusions

In summary, the scope of this thesis was to provide digital twin of a real roundabout scenario and implement it in both a traffic simulator and a driving simulator. To do this, we obtained flow and queue data from the real location. This data was later introduced into a microsimulation scenario and used to calibrate a Car Following Model using SUMO. The results showed that the CFM is able to reproduce the different queues that were measured, although some improvements in the data collection process could lead to more refined models. During this process, the major constraint that we faced was the necessity of using a time step of 0.005 s to match the requirement of the co-simulation scheme. Once the calibration of the traffic simulation is done, the data is sent to perform the training of the automated vehicle policy. After the training of the policy is done, different traffic scenarios with different penetrations levels of automated vehicles can be tested. These tests show that the policy is preferred both in terms of traffic safety and smoothness
Regarding the calibration of the traffic scenario, further improvements could be made. For instance, collecting more data would allow to perform a validation of the obtained parameters improving the training scenario for the policy. Different CFMs could be tested and compare its performance against the IDM, furthermore, it could be possible to use AI training to reproduce the behavior of human-driven vehicles. To overcome the computational burden of repeating costly simulations, it could be possible to use neural networks to try and capture the relationship between parameters and outputs and then implement optimization techniques to look

for an even better set of parameters. We performed some initial attempts, but we were not able to obtain a working model.
In the upcoming months the project will continue to introduce different pieces of required hardware to reproduce the latencies related to the communication process. The effect of this will be assessed in how it affects the performance of the automated vehicles on traffic fluency and safety as well as analyze how the driver perceives the behavior of the automated vehicles. It will also be possible to understand how the passenger of the automated vehicle would perceive the vehicle in terms of comfort and perceived safety, having the passenger in the driving simulator while it responds to the commands of the automated vehicle policy.

References

[1] Stefano Secci et al. A secure and reusable artificial intelligence platform for edge computing in beyond 5g networks. d2.1 use cases, requirements, and preliminary system architecture, 2021.

[2] Department for Transport. Research on the impacts of connected and autonomous vehicles (cavs) on traffic flow summary report department for transport, 2016.

[3] Pablo Alvarez Lopez, Michael Behrisch, Laura Bieker-Walz, Jakob Erdmann, Yun-Pang Flötteröd, Robert Hilbrich, Leonhard Lücken, Johannes Rummel, Peter Wagner, and Evamarie Wießner. Microscopic traffic simulation using sumo. In *IEEE Intelligent Transportation Systems Conference*, 2018.